Management challenges in creating value from business analytics

Richard Vidgen (corresponding author)
School of Business, Economics and Informatics, Birkbeck University, UK &
University of New South Wales Business School, Australia
Email: r.vidgen@unsw.edu.au

Sarah Shaw
Hull University Business School
Email: sarah.shaw@hull.ac.uk

David B. Grant
Hull University Business School/Hanken School of Economics
Email: d.grant@hull.ac.uk

Abstract

The popularity of big data and business analytics has increased tremendously in the last decade and a key challenge for organizations is in understanding how to leverage them to create business value. However, while the literature acknowledges the importance of these topics little work has addressed them from the organization's point of view. This paper investigates the challenges faced by organizational managers seeking to become more data and information-driven in order to create value. Empirical research comprised a mixed methods approach using (1) a Delphi study with practitioners through various forums and (2) interviews with business analytics managers in three case organizations. The case studies reinforced the Delphi findings and highlighted several challenge focal areas: organizations need a clear data and analytics strategy, the right people to effect a data-driven cultural change, and to consider data and information ethics when using data for competitive advantage. Further, becoming data-driven is not merely a technical issue and demands that organizations firstly organize their business analytics departments to comprise business analysts, data scientists, and IT personnel, and secondly align that business analytics capability with their business strategy in order to tackle the analytics challenge in a systemic and joined-up way. As a result, this paper presents a business analytics ecosystem for organizations that contributes to the body of scholarly knowledge by identifying key business areas and functions to address to achieve this transformation.

Key words: analytics, Delphi, management challenges, value creation, ecosystem

Highlights:

- Presents a Delphi study of the challenges of big data analytics
- Provides in-depth background to the challenges via interviews with major big data enterprises
- Provides insight into analytics as a complex socio-technical entanglement
- Develops an analytics eco-system framework
- Gives practical guidance to managers about how they can navigate the organizational journey to becoming data-driven

1 Introduction

We are living in an age of data deluge. Everywhere we go, everything we say, everything we buy leaves a digital trace that is recorded and stored. Consequently, there is much excitement – and some trepidation - around big data and business analytics as organizations of all types explore how they can use their data to create (and protect) value (McKinsey, 2011; Yui, 2012). Data analytic methods are being used in many and varied ways; for example, to predict consumer choices, to predict the likelihood of a medical condition, to detect political extremism in social networks and social media, and to better manage traffic networks. These methods are accompanied by a change in data characteristics (Zikopoulos et al., 2012): (1) volume - increasing amounts of data over traditional settings (e.g., from the Internet of Things); (2) velocity - information is being generated at a rate that exceeds those of traditional systems, and; (3) variety - multiple emerging forms of data, structured and unstructured, such as text, social media data, and video.

While there are numerous definitions of analytics, INFORMS (2016) proposes "Analytics, the scientific process of transforming data into insight for making better decisions" and the Operational Research Society's (2016) "Learn about O.R." Web site says "In a nutshell, operational research (O.R.) is the discipline of applying advanced analytical methods to help make better decisions". According to Davenport and Harris, "business analytics" is concerned with "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (2007, p. 7). A key aspect of all three definitions is that analytics is concerned with decision-making, while Davenport and Harris emphasize that insight needs to be actionable. The introduction of machine learning into analytics further opens up the opportunity for a bottom-up and atheoretical approach to finding patterns in data - an approach that has led to concerns about 'big data hubris', which Lazer et al. (2014) say is the often implicit assumption that big data is a substitute for, rather than a supplement to, traditional data collection and analysis.

Regardless, the opportunities opened up by big data and business analytics are leading academics and practitioners to explore "how ubiquitous data can generate new sources of value, as well as the routes through which such value is manifest (mechanisms of value creation) and how this value is apportioned among the parties and data contributors …" (George et al., 2014, p. 324). McAfee and Brynjolfsson (2012) find that data-driven companies are, on average, 5% more productive and 6% more profitable than their

competitors. However, becoming a data-driven organization is a complex and significant challenge for managers: "Exploiting vast new flows of information can radically improve your company's performance. But first you'll have to change your decision-making culture." (p. 61). This paper aims to investigate the challenges faced by managers in organizations that seek to change their 'decision-making culture' in order that they can become data-driven and consistently and effectively create value from big data analytics. Thus, the research in this paper seeks to provide insights into data-driven organizations through investigating the following questions:

1. How do organizations extract or create value from [big] data?
2. What challenges do organizations face in building their business analytics capability in order to extract or create such value?

Addressing these questions is important as very little knowledge exists, at a granular level, about what big data analytics challenges exist and why. Further, there is a lack of guidance to practitioners on how to address these challenges to 'bridge the gap' in creating business value. Addressing this gap represents a key step change for organizations and is what differentiates the big data analytics exemplars from the rest. The objective of this paper is to provide insight and guidance to firms who wish to make this transformative analytics journey. Additionally, this paper contributes to the body of scholarly knowledge by providing a theoretical framework that identifies the key business areas and functions that must be engaged to achieve this transformation. In the next section we turn to the research background, which will set the scene for the research approach and methodology in section 3. The research design comprises two strands: a Delphi study (section 4) and interviews with heads of business analytics in three case organizations (section 5). The findings are discussed in section 6 and the paper concludes with a summary.

2 Business analytics and value creation

Mortenson et al. (2015) argue that analytics represents the sixth period of the dianoetic paradigm, distinguished by large volumes of heterogeneous data that is complemented by an array of tools for capturing, processing, and visualizing that data. Mortenson et al. (ibid) argue that the OR (Operational Research) community should avoid being 'isolationist' or 'faddist' but address the challenges and opportunities presented by "big data, new data architectures, unstructured data, real-time analytics, and data visualization" (p.

592). However, they conclude that analytics is outpacing OR and Management Science (MS): *" ... OR/MS does not exist entirely in isolation; the community must embrace and engage with the wider concerns of the ecosystem and paradigm or risk declining into obscurity. With other academic and practitioner communities engaging with analytics and increasing research in these areas, OR/MS is in danger of being left behind."* (p. 593).

Ranyard et al. (2015) argue that the operational research (OR) community needs to extend its efforts for practitioners, particularly as regards problem structuring methods (PSMs) or Soft OR and the business analytics movement, to capitalize on the big data and analytics revolution and to be at the forefront of assisting practice with better theory concerning how to obtain value.

Waller and Fawcett (2013) say that data science, predictive analytics and big data – which they collectively refer to as DPB – is increasing in importance for academics as well as practitioners. They cite Barton and Court (2012), Chen et al. (2012), Davenport and Patil (2012) and McAfee and Brynjolfsson (2012) as recent evidence of that importance and note that a new journal, *Big Data*, premiered in 2013. As part of the research for this paper, in 2016 we conducted a review of new journals and found fifteen new journals launched since 2013, including titles such as International Journal of Data Science, Open Journal of Big Data, Journal of Data Science, Big Data and Society, Big Data Research, International Journal of Business Analytics, and the Journal of Big Data.

Waller and Fawcett discuss the importance of DPB to their particular functional community of logistics and supply chain management (LSCM), which has likewise grown in importance for organizations and academics in modern globalized economies that rely on data for basic business transactions such as ordering, payment and tracking and tracing (Grant, 2012). Schoenherr and Speier-Pero (2015) provided a holistic view regarding DPB's current state and future potential for LSCM while at a more tactical level Hazen et al. (2014) discussed data quality and Bendoly (2016) proposed how to better visualize data through the use of semiotics for sense making. Finally, Wang et al. (2016) proposed a research agenda for LSCM researchers. However, from an organizational or practitioner perspective, Watson (2014), recapping Davenport (2006), notes that logistics and supply chain managers are not clear on what analytics and big data mean, nor what value these concepts offer to them and their organization. These issues identified for LSCM are a common theme cutting across many business sectors.

This raises the question of: what comprises value for an organization? Lindgreen et al. (2012) argue that value is the monetary worth of various benefits a customer receives from a product or service, compared to the price paid and the cost of ownership and taking into account competitors' offerings – the premise being that providing more value is a source of competitive advantage. They also argue that the issue of value metrics continues to be important to organizations in an era of exploding data sources, particularly in tactical matters such as stock acquisition and inventory management of fast-moving consumer goods. For example, Pandey (2016) notes 2.5 petabytes of data per hour is being handled by Wal-Mart across its global retail operations. Further, Pape (2016) considers that there is an issue of what data to store in its systems to conduct business analytics to extract value – most data is internally created and there are high costs to generate, clean and maintain new data items as well as simple data storage costs.

Kiron and Shockley (2011) concur and note that organizations have to develop data-oriented management systems to make sense of the increasing volumes of data and address the need to create not only business value but also competitive advantage. In 2011, 57% of respondents to their survey noted their organizations were gaining competitive value from analytics, up from 37% in 2010. Following on from that, LaValle et al. (2011) highlighted three capability levels in organizations to adopt and use analytics – 'aspirational' justifies actions, 'experienced' guides actions, and 'transformed' prescribes actions. To move towards transformed, Shanks and Bekmamedova (2012) suggest that dynamic capabilities, the capacity of an organization to proactively create, extend or modify its resource base (after Penrose, 1959), and business analytics-enabled customer relationship management (CRM) capabilities will lead to business value and improved competitive advantage - if embedded into the culture and processes of a firm over time.

3 Research approach

3.1 Research framework

McAfee and Brynjolfsson (2012) identify five challenges for organizations in becoming data-driven: leadership, talent management, technology, decision-making, and company culture. Clearly, analytics is not simply a technical matter. Nerur et al. (2005) explored the organizational change implications of the migration from traditional software

development to agile software development using a model with four dimensions: (1) organization and management, (2) people, (3) process, and (4) technology. This model has a long and distinguished provenance in socio-technical systems and Leavitt's (1965) diamond model of organization. We use the diamond framework to study the challenges in becoming a data-driven organization. We posit that the business analytics capability of an organization can be thought of as a mediator between the data the organization generates and accesses (internal and external) and the value the organization can leverage from that data through actions based on better decisions (Figure 1).

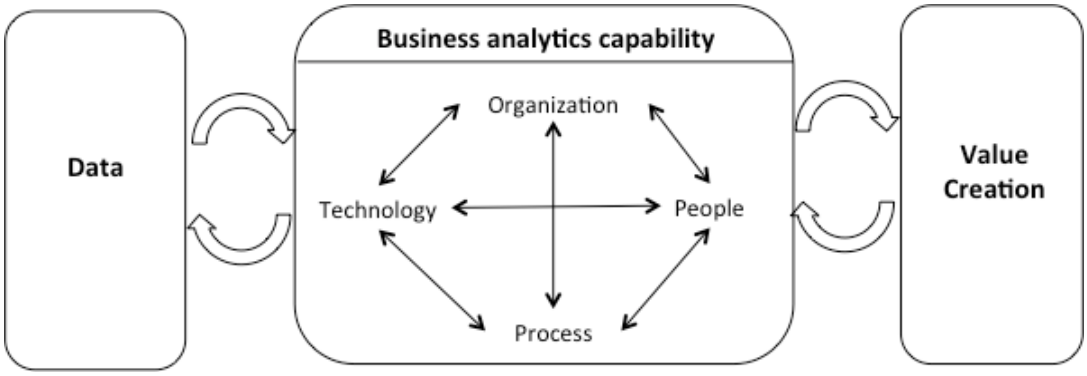

Figure 1: The research framework (adapted from Leavitt, 1965 and Nerur et al., 2005)

3.2 Research design

Given the exploratory, holistic and topical nature of our research issue, and the need to build theory in this relatively new research area, we employ a multi-method approach that combines both qualitative and quantitative methods to identify 1) how organizations extract or create value from data, and 2) the challenges organizations face in building their business data analytics capability to extract or create such value. The research questions themselves inform the choice of paradigm and thus lead to the research methodology (Ellram, 1996; Yin, 2009). Given that the research questions ask 'what' and 'how' type propositions, this also reinforced the need for an exploratory approach. The multi-method research design enabled the authors to alternate between inductive and deductive thought, thus generating a deep and rich picture of this multi-dimensional research problem from different perspectives, providing a basis on which to build theory.

To explore the research questions we followed two methods in parallel: a Delphi study and semi-structured interviews in three case study organisations. As noted by Mangan

et al. (2004, p. 569), the purpose of adopting a multi-method approach in synchrony is the ability to "*compensate for the flaws, and leverage the strengths, of the various available methodologies.*" Thus, the Delphi study helps provide a broad research setting with a relatively large number of respondents while the three case organizations provide the opportunity for depth and exploration, thus enhancing insight and providing more robust results (Craighead et al. 2007). Figure 2 illustrates the research process.

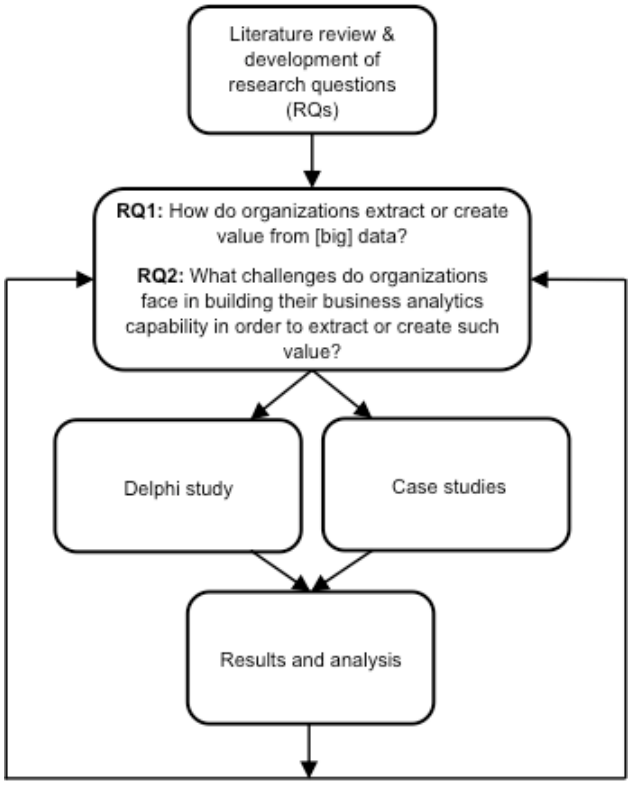

Figure 2: The research design and process

The Delphi Study was conducted with experts selected from big data and business analytics round tables, forums and relevant professional bodies. The purpose of the Delphi Study is to open up and explore the issues of big data and analytics and to understand priorities/areas of concern amongst the experts, thus creating a breadth of knowledge around the two main research questions. Delphi is a survey technique, which uses a combination of qualitative and quantitative techniques to draw upon the opinions of experts about a particular problem or phenomena; its goal is to reach a consensus (Bourgeois et al. 2006; Von der Gracht, 2012). It therefore has the capability to identify and rank a set of management challenges faced by organizations in building their business data analytics capability.

Concurrently and independently of the Delphi Study, semi-structured interviews were conducted with three case study organisations to achieve depth of knowledge around the two research questions and to help contextualise and understand the key themes emerging. Interviews represent a powerful way to elicit narrative data that enables researchers to investigate people's views in depth (Kvale, 2003; Alshenqeeti, 2014). It also assists those being interviewed to "*speak in their own voice and express their own thoughts and feelings*" (Berg, 2007, p.96) about a particular research issue, which was essential in unpacking the challenges around big data and analytics. The interview questions were guided by the research framework in Figure 1 and an interview guide (see Vidgen (2014b) for further details).

4 Delphi study

The Delphi technique was employed to reach a consensus about the relative importance of the key challenges facing organizations in creating value from big data analytics and to assess if these mirrored the important constructs/themes emerging in the case organization interviews. Delphi is an inductive and data-driven process and is a very efficient and effective way to canvas opinion from a large group of experts on a specific problem. The Delphi process involves building consensus through a series of structured questionnaires (Dalkey and Helmer, 1963; McKenna, 1994; Akkermans et al. 2003). Von der Gracht (2012) identifies four characteristics of Delphi studies: anonymity, iteration, controlled feedback and a statistical group response. Paré et al. (2013) also distinguish between four Delphi types: classical, policy, decision, and ranking. In the ranking-type Delphi the objective is to identify and rank key issues using experts in order to guide future management action and to inform research agendas – this is the goal of the current paper. Delphi ranking is the most common form of Delphi in IS research (Okali and Pawlowski, 2004) and consists of three steps: 1) brainstorming, 2) narrowing, and 3) ranking (Figure 3).

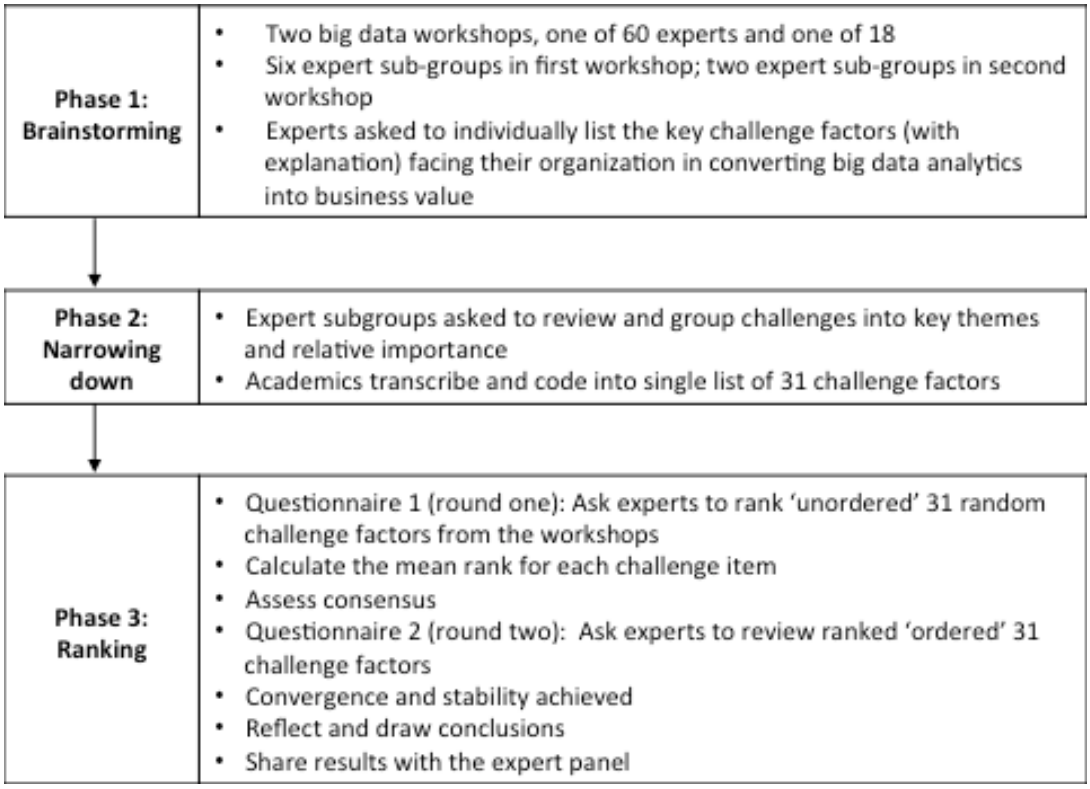

Figure 3: Delphi study process used in this study (adapted from Okali and Pawlowski, 2004, p.24)

4.1 Brainstorming

The success of the Delphi technique is reliant on the selection of appropriate experts (Jacobs, 1996; Melnyk et al., 2014). Two workshops took place. The first workshop was held as part of the Hull Analytics Forum in July 2014 (Vidgen, 2014a) with 60 participants organized into six groups; the second workshop was held at the OR56 conference in September 2014 as part of the 'Making an Impact' stream (Vidgen and Morton, 2014) with 28 participants organized into three groups. The workshop participants comprised OR practitioners, consultants, academics, and user representatives of organisations considering the adoption of big data and predictive analytics (some had already started on the journey). The expert demographics ranged from Heads of Information Management through to Data Architects and Analysts, from a variety of industrial sectors and company sizes. For each workshop, the experts were divided into sub-groups, assigned a facilitator and asked to identify, using Post-it notes, as many current challenge factors faced by their organisation in building a business analytics capability from Big Data. The experts provided a brief title and sentence to explain the rationale for each proposed challenge factor identified (Delbecq et al., 1975; Schmidt, 1997).

4.2 Narrowing

Within the sub-groups, the experts were asked to cluster each of the challenge factors into major constructs/themes and rank these themes in terms of relative importance. This led not only to the identification of challenges, but also generated insight into why certain challenges were viewed as more important than others (Keil et al., 1998). All groups then reflected upon and checked their respective group's outputs at the end of each workshop. Data from the two workshops were fully transcribed into a spreadsheet and coded independently by three academics using the data reduction, data display and conclusion drawing/verification technique described by Miles and Huberman (1994).

The Miles and Huberman (1994) qualitative data process encompasses three distinct activities: data display, data reduction and conclusion/verification. For this study, the data display process involved the workshop experts reviewing and reflecting on the displayed qualitative data during the workshop (both in their own group and others) to develop clusters from the Post-It notes; this formed part of the initial data display and data reduction elements. The subsequent clusters and individual Post-It notes were then transcribed into a spreadsheet and reviewed independently by three academics after the workshop. The objective was to tease out, remove duplicates, summarise and categorise the challenge codes, to reduce the data further. Finally, the three academics reviewed their spreadsheets collectively as a team, to firstly agree upon a final set of challenge codes for the Delphi Study and secondly to make sense of and verify the meanings emerging from this set of unique challenge codes. The coding process resulted in a single list of thirty-one unique challenge codes and descriptions for subsequent ranking by questionnaire.

4.3 Ranking

Two Delphi ranking rounds were completed using an online survey questionnaire to order the thirty-one challenge factors in terms of their perceived significance in creating value from big data analytics. The questionnaire was pilot tested with ten academics for content validation and usability prior to being released. The pilot testing indicated that ranking 31 randomly ordered items would be time-consuming and cognitively challenging. In round one, to improve data quality and to reduce drop-out rates, respondents were asked to

select their 'top 10' items and to then rank these (see Appendix A for details). In round two respondents were presented with all thirty-one items in rank order and respondents were asked to reorder the items using the 'drag and drop' facility in the survey builder software.

The first round of the Delphi study resulted in seventy-two fully completed responses. The respondents comprised 36 practitioners, 23 consultants, and 13 academics. Respondents were given the opportunity to propose new challenges, although none took this up. The challenges from the first round were ordered by mean rank importance in the second round to facilitate a development of a consensus (Schmidt et al., 1997; Paré et al., 2013). The second round produced forty-two responses. Sufficient convergence and stability was achieved in round two to close the Delphi study (Von der Gracht, 2012).

4.4 Implications of the Delphi study

The 31 items identified in the Delphi study are presented in Appendix B in rank order of importance together with the descriptions of the items provided to respondents. The top 5 issues are: (1) Managing data quality, (2) Using analytics for improved decision making, (3) Creating a big data and analytics strategy, (4) Availability of data, and (5) Building data skills in the organization. We then coded the 31 items from the Delphi study according to our model in Figure 1. Three academics coded the items and then discussed points of difference to arrive at the coding shown in Table 1. While most of the items sit comfortably in one area it is clear that some span constructs, e.g., 'producing credible analytics' relates to the analytics process but also is key to value creation. However, most items found a good fit under a single construct. The analysis shown in Table 1 indicates that, based on an average rank per category, that 'value' and 'people' are the most important challenges organizations face in converting big data and analytics into business value.

While the absolute number of value issues is low, all three items are ranked highly in importance (an average value of 6.0), with 'using analytics for improved decision making' ranked the second most important challenge. Similarly, the number of people issues is also low, but the items are again ranked highly in terms of importance (an average value of 9), indicating that organizations must acquire the right people, with the right skills to support their analytics transformation. While the technology category contains only two items it highlights important challenges for managers (average value of 13.0): addressing the restrictions of existing IT platforms and coping with large volumes of data. Data issues are

numerous and important (average value of 13.29) and follow closely on from technology, with 'managing data quality' the highest ranked challenge identified by managers (discussion of which dominated the Delphi workshops). Improving the quality and credibility of data is a key enabler and potentially a barrier to value creation from big data and business analytics. Many of the issues discussed around data quality, related to data sources, data ownership/governance and obsolete data held on legacy systems.

Process issues are generally lower in number and lower in ranking (average value of 20.0), a situation that may change as organizations embark on, and get further into, their analytics transformation. Organization issues follow closely on from process issues and dominate in number (average value of 21.0), indicating that organizational transformation will likely be a complex challenge for analytics transformation. A specific and significant managerial challenge for organizations is 'creating a big data and analytics strategy' (ranked third overall). For managers, this issue represents a key starting point in the transformational journey, and one in which a top-down approach is likely required, spearheaded by a business leader, to get 'buy-in' from the rest of the organization. Also, having a clear strategy and business case in place would enable other key actions/decisions to be addressed, for instance 'overcoming resistance to change' and 'building a corporate data culture'. People (employees) will act as 'champions for change', which is an essential part of any change management programme.

Category	Rank/ average	Item	Rank
Value (3)	1 (6.0)	Using analytics for improved decision making	2
		Measuring customer value impact	7
		Establishing a business case	9
People (3)	2 (9.0)	Building data skills in the organization	5
		Analytics skills shortage	8
		Technical skills shortage	15
Technology (2)	3 (13.0)	Restrictions of existing IT platforms	6
		Managing data volumes	20
Data (7)	4 (13.29)	Managing data quality	1
		Availability of data	4
		Getting access to data sources	10
		Managing and integrating data structures	17
		Managing data security and privacy	18
		Data visualization	19
		Defining what 'big' data is	24
Process (4)	5 (20.0)	Producing credible analytics	11
		Managing data processes	14
		Manipulating data	26
		Performance management	29
Organization (12)	6 (21.0)	Creating a big data and analytics strategy	3
		Building a corporate data culture	12
		Making time available for analytics	13
		Overcoming resistance to change	16
		Agreeing data ownership	21
		Managing costs of analytics	22
		Defining the scope of analytics projects	23
		Securing investment	25
		Legislative and regulatory compliance	27
		Using the data ethically	28
		Safeguarding reputation	30
		Working with academia	31

Table 1: Thirty-one Delphi items grouped by research construct

In summary, the Delphi study identified numerous challenges which organizations face in creating value from big data and analytics. The categories of value and people generate the overall highest average ranking in Table 1 and these dimensions may therefore be crucial in converting big data to business value. However, other important individual challenges emerged and are prominent. Firstly, data quality is absolutely essential and must be addressed if organizations are to create value from their data. Secondly, using analytics for

improved decision-making is paramount to managers. Finally, creating a big data and analytics strategy represents a key starting point to obtain organizational buy-in overall.

5 Management issues in analytics - case studies

To explore the role of the business analytics function more deeply we investigated three case organizations (see Vidgen (2014b) for further details). This research design is best suited when a contextual understanding of an existing reality is desired (Yin, 2009). Further, it allows gaining deeper and richer insights into emergent phenomena (Willis et al., 2007). Thus the aim of the research is to gain a deeper understanding and insight into the change implications for firms that seek to create value from their data.

Data were collected over four months via interviews with the senior manager responsible for business analytics at three organizations. The data collection was guided by an interview guide that contained open-ended questions to encourage interviewees to share their opinions and experiences with us (Yin, 2009), but also to allow the researchers to further explore emergent themes. The interview guide was used as a structure and aide memoire for the interview rather than as a rigid template. Each interview lasted between 50 to 100 minutes and was electronically recorded. All interviews were subsequently professionally transcribed.

To analyze the data, we utilized Strauss and Corbin's (1998) open coding and axial coding techniques. Hence, we sought to identify codes and categories on analytics not purely from the data, but rather based on the dimensions in Figure 1. During open coding, we first deconceptualized data by breaking it into smaller units that were repeatedly compared, categorized and reexamined again based on the dimensions of Figure 1. During axial coding, we then reconceptualized the data in new ways that enabled connections between categories to emerge, that is the different categories were assembled into higher-order themes to give meaning to business analytics and the value creation process. Throughout the data analysis we followed guidelines by Miles and Huberman (1994) regarding evaluation criteria of qualitative research (e.g., authenticity, plausibility, and transferability).

The case organizations were selected on the basis that they are large (i.e., can generate big data) and that they have an established business analytics function. Our three cases are, pseudonymously, MobCo (a mobile telecoms company), MediaCo (a broadcaster), and CityTrans (a transport provider for a large city).

MobCo is a large international mobile telecoms provider whose primary focus is selling airtime to consumers. MobCo has a substantial share of the UK market and revenues in the billions. The mobile phone network creates a vast amount of data associated with mobile phone usage; data that can be used in many ways by MobCo to support network operations, billing, and customer service. The network also allows the location of users to be tracked: by triangulating from mobile phone base stations the user of a device can be identified to an accuracy of 50 meters.

MediaCo is a broadcaster (television company) whose revenue is primarily gained from selling advertising. MediaCo delivers content through the digital terrestrial network and via the Internet as an 'on demand' service. Through the Internet on demand service MediaCo can capture details of users' viewing habits, which allows MediaCo to place appropriate adverts and to promote content to its viewers through recommender applications. MediaCo is also engaged in promoting societal change and thus helping users discover content that goes beyond simple entertainment is an important part of its mission.

CityTrans is a governmental, not-for-profit provider of an integrated public transport system for a major city, dealing with every aspect of how people move across the city using different modes of public and private transport. The organization works with many data sets, such as network operations, travel data, traffic data, load weight data, infrared data, and customer data. Some of these data sets have been linked together for operational analysis and planning, but there are still a number of unexplored opportunities in joining up these numerous and diverse datasets. CityTrans collects the bulk of its public transport travel data through a smart travel card (STC), which can be used anonymously or as a registered (and therefore identifiable) customer.

The cases were analyzed individually (Vidgen, 2014b) prior to conducting a cross-case analysis (Eisenhardt, 1989). From the summaries of the cases twenty-one recommendations were identified, which, following the research model presented in Figure 1, are grouped into: (1) data and value, (2) organization and process, (3) people and technology.

5.1 Data and value

The three case organizations identified numerous opportunities for value creation as shown in Table 2, covering a range of tangible, intangible and wider societal benefits of business analytics.

Case	Sources of value from analytics
MobCo	• Internal - improved network operations enabling better data and services to be offered to existing mobile phone users and to attract new users • External - creation of data products based on mobile phone usage and location awareness (e.g., anti-credit card fraud, location-based marketing) • Potential for public service offerings (e.g., flood warning by text message)
MediaCo	• Increased advertising revenues • Marketing and promotion of content • Social benefit through education (promotion of content novel to viewer)
CityTrans	• Improvements to reliability and quality of service • Insights into the specific customer experience (not an averaged out experience) • Replacement of expensive qualitative surveys by automated travel analysis • Potential to initiate behavioural change in passengers and spread the network load

Table 2: Sources of value from analytics

All three cases reported concerns about the quality of their data (Table 3), similar to observations made in the Delphi study. In particular, they were concerned about the currency of the data (e.g., from real-time systems) and its consistency (data is held numerous times in different systems and ascertaining a single point of truth can be difficult). While the data is not expected to be perfect, it must be fit for purpose (Strong et al., 1997; Haug and Arlbjørn, 2011). Further, better quality data will reduce the time needed to clean and pre-process data making more time available for value added analysis and modeling.

Data and value	
1 Data quality	Data must be 'fit for purpose'. Analytics teams can spend up to 90% of their time manipulating and cleaning data in preparation for analysis and modeling. Improving data quality will increase the time available for modeling.
2 Permissions platforms	Organizations will develop customer self-serve permissions portals. Assurance of trust is paramount – organizations must be transparent about how data is used and generate trust that it is secure
3 Value sharing	Value created from data may need to be shared with the data originator
4 Data partnerships	Value is likely to arise from data partnerships rather than selling data as a commodity to third parties
5 Anonymization and retention policies	Establish confidence in the data anonymization process before data is shared
6 Public and private value	The data managed by the organizations can be used for public and societal benefit as well as commercial benefit (e.g., flood warnings)
7 Legislation and regulation	Changes in legislation may result in fundamental shifts in what can be done with customer data (for example a "right to be forgotten")

Table 3: Data and value

The respondents highlighted concerns about how customer data is used and the need to be transparent. MobCo plans to go a step further and seek customer permission on data usage:

> *"… we are launching a new permissions platform and if you are a MobCo customer you will see your personal details … you can log on, enter your credentials, and you will see all the data that we hold about you." (MobCo)*

Such a platform would allow customers and other data owners to opt in and opt out. It is also likely that customers will expect to be incentivized or compensated for the use of their data in ways that go beyond simply receiving a better service, i.e., the value created from data may need to be shared with the customer. We found that the case organizations saw selling customer data as a low value activity that could harm the image of the organization. Rather, they were more likely to enter into value creating partnerships, e.g., using location based services to reduce credit card theft:

> *"So you check into a hotel, give them your card, the merchant will dial up to Visa and say, "Here is this person's card," and Visa will do, right now, will do a fraud check. If they know that you're standing right in front of that merchant, that will eliminate almost all fraud." (MobCo)*

When data is shared with research partners it has to be anonymized and this may need to go beyond simply stripping out personal identifiers such as names and addresses if the risk of reidentification is to be managed effectively (Ohm, 2010).

While CityTrans' mission is to provide an integrated transport system for the passengers and travellers in the city, the public service agenda applied also to the two commercial organizations. MobCo could envisage using its location-based services to warn of floods and tsunamis, while MediaCo wanted to actively influence viewing habits from an educational and social awareness agenda:

> *"it isn't about just because I watch comedy you're not introducing me to more and more and more comedy, you're helping me to discover something in factual perhaps that I would never even consider. And I may not enjoy it but it perhaps will evoke some kind of reaction." (MediaCo)*

The respondents were very much aware of the need to comply with legislation and of potential changes to legislation, such as the 'right to be forgotten', which may require them to not only change the data they retain and how they use it, but could have significant impacts on their data-driven strategies and business models. Indeed, MediaCo saw this as a potential source of competitive advantage that they could "get to a point where we saw no PII [personal identifying information] at all" and that it would be "highly advantageous as a brand to be able to go to market and say look, we are no longer storing any of your information".

5.2 Organization and process

Our respondents see the need for an articulation of a data strategy (Table 4) with a clear idea of how value will be created from data, whether that is financial (e.g., increased revenue, decreased costs), intangible (e.g., increased customer satisfaction), or societal (e.g., Tsunami warnings). This reinforces the findings from the Delphi study, where managers ranked 'creating a big data and analytics strategy' as the second most important challenge. The case organizations recognize that implementing a data strategy will require deep-rooted organizational and cultural change taking years rather than months (Adler and Shenhar, 1990). The heads of analytics see themselves as champions "trying to garner support for creating [an] integrated analytic strategy" (MobCo).

Organization	
8 Corporate analytics strategy	An analytics strategy is needed with a clear articulation of how and where value will be created
9 Organizational change	Becoming a data-driven organization will involve organizational and cultural change and innovation
10 Team structure	The business analytics team requires a mix of data scientists, business analysts, and IT specialists
11 Deep domain knowledge	The business analytics function will need to build deep understanding of the organization and its business domain if it is to create lasting value
12 Academic partnering	Data science expertise and resource can be acquired through partnering with Universities
Process	
13 Ethics process	Ethics committees should be established to provide oversight of how data is used and to protect the reputations and brands of organizations
14 Agility	The agile practices of software development can be adopted and modified to provide a process model for analytics projects
15 Explore and exploit	Analytics teams should exploit in response to identified problems (80%) and have slack resource to explore new opportunities (20%)

Table 4: Organization and process

We found the structure of the analytics teams was similar in all three organizations, comprising data scientists, business analysts, and IT services. The data scientists require data, statistical, and IT skills to support data acquisition, data preparation and model building. The business analysts need deep domain knowledge and a focus on creating business value; they work with the business to understand requirements and with data scientists to shape solutions. To turn data science prototypes into production applications and data products requires IT professionals. CityTrans report that the resources and expertise of the analytics team is augmented with partnerships with research institutions (e.g., doctoral students), allowing them to experiment and tackle projects that might not otherwise be viable.

All three cases were concerned with how the data collected is used and the impact it could have on the trust of customers and perceptions of the brand image of the organization. While some things may be legal and acceptable within the regulatory framework they may not be in accord with the values of the organization and the image that it wants to project; MobCo commented that it was acceptable for customers to think that their use of data was "spooky" ("how *do* they do that?") but they did not want this to tip over into "creepy" ("ugh, how do they do *that*?"). The case organizations expressed concern with ethics and data governance and recognized the need for an ethics committee to consider requests to use data for commercial purposes and assess whether it is legal, whether it is in accord with the values of the organization, and the potential risks (e.g., to the brand value).

All three case organizations want their software development process to be agile as opposed to waterfall and to allow space for exploration of new ideas. Data science projects can learn much from agile software development, which has a proven and tested process model for delivering software that creates business value through iterative delivery rather than the stepwise definition and execution of a specification. Many of the values and practices from agile software development can be adopted in data science projects. For example, agile methods, such as eXtreme Programming (XP) and Scrum, emphasize: engagement with the customer (or subject matter expert), frequent delivery of working software (or data science solutions), co-location of resources (e.g., subject matter expert, business analyst, and data scientist), learning through rotation of roles (e.g., data scientists can learn new techniques from other data scientists), and establishing a culture of professional excellence (Vidgen and Wang, 2009). As well as being agile, a truly effective data science team will explore as well as exploit; while the bulk of an analyst's time, say 80%, is spent working with data to solve defined business problems, the remaining time, say 20%, should be retained as slack resource for experimentation and exploration – such as searching for new patterns in the data, trying new tools, and learning new techniques.

5.3 People and technology

The overriding message from the cases (Table 5) is that organizations want data scientists who are curious:

> *"… a lot of my analysts certainly will describe how they were just fundamentally curious around how the world is structured, or curious as to why, you know, patterns emerge the way they emerge. So it wasn't about the vocation necessarily itself, but it was an element of curiosity. And that curiosity is what you want in an analyst." (MediaCo)*

People	
16 Data scientist personal attributes	The data scientist must be curious, problem-focused, able to work independently, and capable of co-creating and communicating stories to the business that form the basis for actionable insight into data
17 Data scientist skills	The ability to program, e.g., using R, and strong statistical skills
18 Data scientist as 'bricoleur'	The tools and techniques don't matter as much as the ability of the data scientist to cobble together solutions using the tools at hand ('bricolage')
19 Acquisition and retention	Data scientists are attracted by interesting data to work with and retained if they are given interesting problems to work on and have career paths
Technology	
20 Visualization as story-telling	Visualization of data is not simply a technical feature – it is part of the story-telling
21 Technology selection	While technology is in a state of flux an agnostic approach is preferable

Table 5: People and technology

Respondents stressed that data scientists should also have a problem-solving orientation, be capable of independent working, and be able to work with the business to co-create plausible and convincing stories through data that lead ultimately to actionable insights:

> *"You need to have the story about what does this mean for your organization and what action decision-makers should take. Your data scientist needs to take the complicated maths and explain the conclusions in such a way that someone who is not a data analyst can understand it. In some ways, that may be the hardest skill for the data scientist" (CityTrans)*

While the data scientist undoubtedly needs strong statistical and mathematical skills they also need IT skills, notably an ability to program (e.g., R) and an ability to manipulate data (e.g., SQL). However, rather than rely on one tool, whether it be an enterprise product such as SAS or an open source product such as R, the data scientist needs to be able to use the most appropriate tools to hand, to combine different technologies, toolsets, and analytic techniques to fashion a local and relevant solution. Thus, the data scientist is more 'bricoleur' than engineer. This reinforces a key challenge from the Delphi study, in that 'building data skills in the organization' is fundamental to the transformational journey.

There will be intense competition for data scientists that are technically competent and able to create innovative and practical solutions to business problems through data analytics. CityTrans believes that firms that have interesting data will have an edge in attracting good data scientists; firms that let their data scientists work on interesting problems and build a strong culture of data science professionalism will be better placed to retain their

data scientists. MediaCo believe that some level of movement of data scientists will be positive, as experience in one sector is applied to another. All three cases identify the need for data scientists to have career paths; CityTrans suggests that this will encompass paths to becoming a senior data scientist, becoming a manager of data scientists, becoming a business analyst/strategist, or moving to work in the business as an analyst or manager.

From a technology perspective, visualization and data interaction are more than technical ways of presenting data to the business– they are an integral part of the communication process in which non-technical business people can engage in discussions about data:

> *"… one of our data scientists has built out there just a visualisation using some gravity modelling, just a visualisation of content clusters. And that's, that was developed just to showcase visualisation as a concept, but as a result of that it's now having, it's been touted around the business and it's inspiring quite interesting conversations." (MediaCo)*

As for the underlying big data technologies, these are in a state of flux and will take some time to shake out and making bets on which technologies will win out is a risky proposition. While not all organizations will be able to be agnostic about the technology, as MobCo is, these decisions should be made on the basis of data requirements and the value that can be created from that data rather than fashion.

In summary, the case studies have highlighted challenge focal areas, which are reinforced by the Delphi study. Firstly, organizations need to have a clear data strategy if they want to be data-driven. Secondly, organizations require the right people, with the right skills to effect and drive the data-driven cultural change, these people maybe unique and potentially in short supply, so up-skilling maybe required. Thirdly, although data is a source of competitive advantage, there is a fine balance between value and ethics, particularly from a customer point of view. Finally, although technology is important, it represents only one of many challenges that organizations must address if they are to become data driven.

6 Discussion

The core contribution of this research has been the identification of thirty-one key challenges that organisations face in building their business analytics capabilities (RQ2) and twenty-one corresponding recommendations that organisations can follow to extract or create big data into business value (RQ1). Success in business analytics is a complex matter,

depending on a firm's ability to harness 'simultaneously' multiple resources and capabilities (people, process, technology and organisation) within a business context, including the data itself (the input and raw material), and deploy these synergistically (key actions and decisions) to deliver a valued output as shown in Figure 1. For instance, the top three challenges highlighted by the Delphi study are inextricably linked and represent key steps in the data analytics journey: (1) data quality, (2) using analytics for improved decision making, and (3) creating a big data and business analytics strategy. Data quality is driven by a number of factors, such as old legacy systems, the way in which data is managed and owned, all of which could be rectified by having a clear business analytics strategy. Thus, creating a clear analytics strategy (whether top-down or bottom-up or a combination of the two) is a key starting point in the big data and business analytics transformational journey.

The most prevalent and significant issues associated with 'big data' (data quality, availability of data, and access to data sources) identified in this study are perhaps indicative of the evolutionary stage organisations are at in the big data and business analytics journey. Many organisations are still at a reactive 'baseline analytics' stage (Kiron and Shockley, 2011), grappling with the issues of the data itself and not necessarily tackling this business issue logically, in a top-down or strategic way. This narrow focus reinforces the timeliness and relevance of this paper in identifying key recommendations for creating a business analytics capability. This is further reinforced by the organisational challenges identified in the Delphi study (Table 1), which highlights that a concerted organisational effort, and not just departmental, is required to tackle the challenges in converting big data and analytics into business value.

This research has also provided key insights into the future skill sets needed by organizations in terms of challenges faced by them in building an analytics capability. Analytics skills shortage was identified as a key challenge to practitioners in both the Delphi study and case studies. Being a data scientist is not merely about being good with numbers, they also need to be a 'bricoleur', be curious, problem-focused, able to work independently, and capable of co-creating and communicating stories to the business that form the basis for actionable insight into data. Future data scientists must have the ability to work cross-functionally across business silos and focus on the end goal, i.e., creating solutions and delivering business value. Their role and remit extends beyond the boundaries of the IT department. This has significant implications on the future of the data scientist role, such as recruitment, training and managing the analytics talent pipeline, and thus, the HR strategy. In

order to achieve a data-orientated culture, organizations need competency in information management and analytic expertise (Kiron and Shockley, 2011; Pape, 2016).

While this by no means represents an entire list of challenges or a panacea for addressing big data and building a data analytics capability, this study does provide one of the first empirical insights into a comprehensive and apposite list of challenges and recommendations that will guide practitioners, across a range of sectors, in how to create value from big data and business analytics. The themes emerging from the Delphi largely mirrored those identified in the case studies indicating that theory saturation had been met and, therefore, it is likely that the themes do indeed represent the key challenges facing practitioners in organizations today.

Often, firms have viewed and tackled big data and analytics purely as an IT departmental issue, but it extends far beyond this, and organisations need to 'strategically align' all resources to tackle this issue systemically and in a joined-up way. The resource-based view (RBV) of a firm is an important theory in understanding this data analytics challenge. The RBV theory proposes that firms are comprised of a set of resources or assets -, including those related to data and analytics - that need to work collaboratively together to deliver capability around a given task (Penrose, 1959). Those organisations that perfect this strategic approach will generate a rare, valuable, non-substitutable ability to leverage business value from big data analytics, thereby generating competitive advantage. Given this theory and our empirical findings, we derive an integrative ecosystem shown in Figure 4 for a business analytics strategy, which can be clearly seen to form part of an organization's overall strategizing.

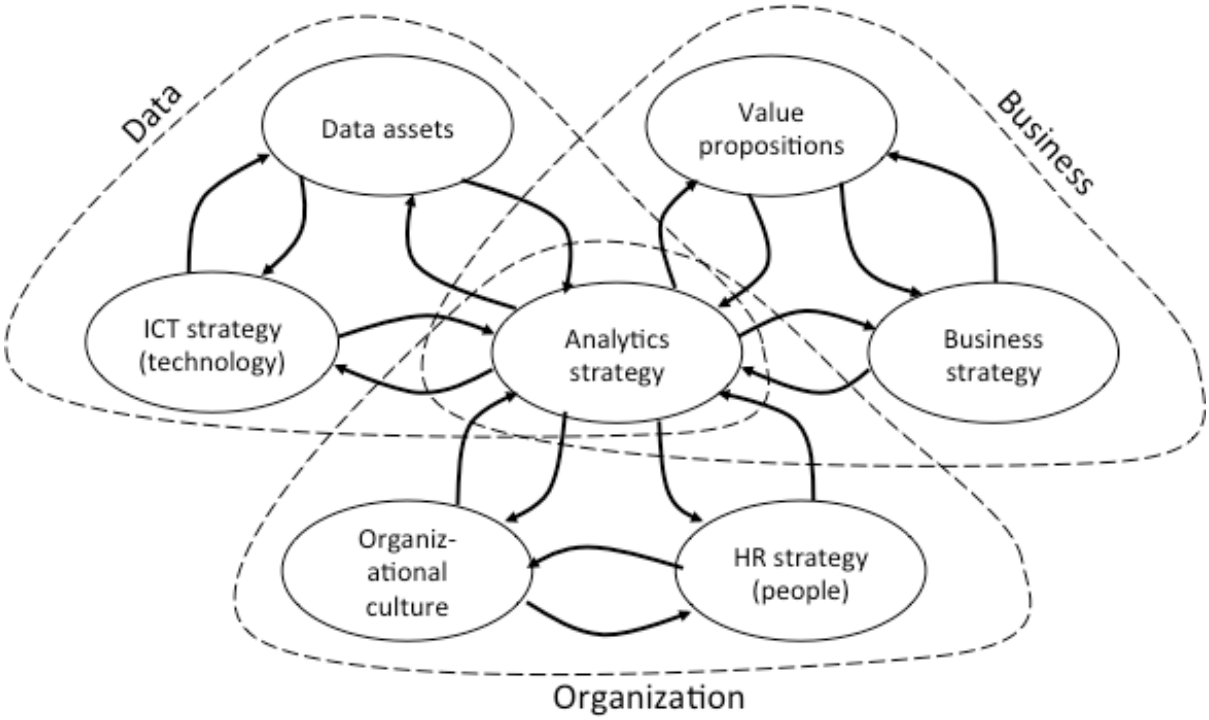

Figure 4: Business analytics as a coevolving ecosystem

The elements of Figure 4 reflect the themes identified from our empirical findings. Data resources require an evaluation of data availability and access to data sources, managing that data's quality, and dealing with restrictions of extant IT platforms. Organizational resources are driven by people and culture to build data and analytics skills in the organization as well as dealing with current skills shortages. The resultant output for businesses comprises establishing a business case for their overall business strategy by using analytics as a tool for improved decision-making and measuring the impact on value creation. The intersection of these three elements is the creation of a big data and analytics strategy to transform data resources into desired outputs. Figure 4 further highlights that organizations not only need to develop business, ICT, HR, and analytics strategies but also that these strategies need to be aligned.

Business ecosystems can be complex and, faced with this data 'torrent' revolution, organizations must quickly adapt to the new system dynamics and environment to survive. In order to deliver an effective business analytics strategy, all of the elements or agents for change within the business ecosystem must interact, coevolve and mutually adapt to leverage and deliver analytics value (see, for example, Vidgen and Wang's (2006) application of coevolution to agile software development and Vessey and Ward's (2013) application to the alignment of IT and business strategies). In coevolutionary theory change is reciprocal;

changes in species A set the stage for the natural selection of changes in species B, and later changes in species B in turn set the stage for further changes in species A (Bateson 1979, p. 227). Coevolutionary interactions between species have the potential to drive rapid and far-reaching change. However, unlike adaptation to a physical environment, adaptation to another species can produce reciprocal evolutionary responses that may "either thwart these adaptive changes or, in mutualistic interactions, magnify their effects." (Thompson, 1999, p. 2116). Thus, hiring excellent data scientists may well put selection pressures on the ICT department (e.g., to provide big data technologies) and the business (e.g., to build analytics into their business processes) but such outcomes are not guaranteed – reciprocal evolutionary responses may indeed thwart attempts at adaptive change.

6.1 Implications for managers

Firstly, Table 1 provides useful guidance to managers on factors to consider when embarking upon their big data and analytics transformational journey. The top five items provide a focus for management attention: data quality, using analytics for improved decision making, creating a big data and analytics strategy, making data available, and building data skills in the organization. Secondly, Tables 2 through 5 provide a wide-ranging checklist of factors that managers should consider when developing the analytics capability of their organization (e.g., what data partnerships might be entered into, what are the legal and regulatory aspects of data use, how can ethical data use be assured). Thirdly, the research shows that business analytics is not a technical project that can be given solely to the IT department. Analytics is more appropriately seen as a business transformation initiative that requires an analytics strategy, senior management support, and active and careful change management (Thorp, 1998). This is not to say that IT is unimportant; it is a fundamental enabler of the business analytics process and essentially embedded in the organization's processes and practices (McAfee, 2006). Fourthly, our research shows that business analytics and data science are overlapping but distinct concepts. Business analytics departments are found to comprise business analysts (who communicate with customers and understand their requirements), data scientists (who work with data and models), and IT staff (who develop and deploy the data science solutions). Thus, making insight *actionable* (Davenport and Harris, 2007) takes more than simply setting up a data science team. Finally, we find that business analytics is a complex undertaking that will entail coevolutionary change involving

– at the very least – alignment of business, IT, and human resources. Implications for researchers and opportunities for future research

6.2 Implications for researchers and opportunities for future research

Firstly, the research contributes by elaborating on a theory of data and business value. The Delphi study and the cases identify factors that can be used to develop quantitative models of analytics value creation that can be subjected to hypothesis testing. The data for such models would typically be collected through surveys of managers with the content being formed by the results of this research (for example, the results of the current research are being used to construct an analytics capability assessment instrument). Secondly, couching business analytics development as a coevolutionary process drawing on a resource-based view of the firm provides a rich way of conceptualising how organizations can build their analytics capability and transform into a data-driven organization. Thirdly, we make a small but useful contribution to the Delphi methodology in producing a lightweight, low cognitive load approach to ranking multiple items (Appendix A).

6.3 Limitations

Notwithstanding the valuable and in-depth insights the case studies bring to a relatively new research area, only three case studies were deployed as part of this study. While the number of cases studies in an exploratory investigation is not reducible to a question of sample size (rather it is about representativeness and achieving saturation) we recognize that there is an opportunity to extend this work to include case studies from other industry sectors, countries and contexts. Bazeley (2007, p. 23) points out that when investigating social life we of necessity bring with us our own lenses and conceptual networks (that is, we enter a situation with 'muddy boots'). The use of a framework also stops us being overwhelmed by the complexity of the situation we are seeking to observe and make sense of. Thus, we used a theoretical framework (Figure 1) as a guide and sensitizing device for the research. However, the use of such a framework can also constrain and bias the collection and interpretation of data. To address this risk the interview protocol was used as a basis for a free-ranging discussion about the role of analytics in the case organizations (rather than a rigid template). In analyzing the data we looked for themes in the data without reference to the research framework and then used the framework to categorize the findings. This approach allowed us to remain open to looking outside of the framework at the data

collection and data analysis stages and to be wary of falling into the trap of ignoring data that did not fit into the constraints of our sensitizing device.

7 Summary and future research

We conducted a Delphi study investigating barriers to value creation with big data analytics, conducted case study interviews, and triangulated the findings around a conceptual model of analytics based on a socio-technical perspective. While not wishing to marginalize analytics technologies and data science methods, this research demonstrates that there are many avenues for future research, including: value sharing models, regulatory impacts, societal benefits/dis-benefits, ethics, assessment of business analytics maturity, business analytics and organizational change, business analytics project management, data quality, human resource development, and visualization in the context of effective story-telling. We also call for a continued injection of theory into analytics research, such as coevolutionary and socio-technical theories, to study the emerging and important practice of business analytics.

8 Acknowledgments

This research was conducted with support from the EPSRC's NEMODE (New Economic Models in the Digital Economy, Network+) programme. John Morton of CPM Consulting helped run the Delphi workshops and provided invaluable feedback on drafts of working reports. We thank researchers from the University of Hull who facilitated Delphi workshops at the Hull Analytics Forum: Pervaiz Akhtar, Dionisis Demetis, Ashish Dwivedi, Risto Talas, and Yasmin Merali.

9 References

Adler, P.S. & Shenhar, A. (1990). Adapting your technological base: The organizational challenge. *Sloan Management Review*, 32 (1), 25-37.

Akkermans, H.A., Bogerd, P., Yucesan, E. & Wassenhove, L.N. (2003). The impact of ERP on supply chain management: exploratory findings from a European Delphi study. *European Journal of Operational Research*, 146 (2), 284-301.

Alshenqeeti, H. (2014), *Interviewing as a Data Collection Method: A Critical Review.* English Linguistics Research, 3(1): 39-45.

Barton, D. & Court, D. (2012). Making Advanced Analytics Work for You. *Harvard Business Review*. 90, 79-83.

Bazeley, P. (2007). *Qualitative Data Analysis with Nvivo*. Sage, Thousand Oaks, CA.

Bourgeois, J., Pugmire, L., Stevenson, K., Swanson, N. and Swanson, B., (2006). *The Delphi Method: A Qualitative Means to a Better Future*, available at: http://www.freequality.org/documents/knowledge/Delphimethod.pdf [accessed 21 May 2016].

Bendoly, E. (2016). Fit, Bias, and Enacted Sensemaking in Data Visualization: Frameworks for Continuous Development in Operations and Supply Chain Management Analytics. *Journal of Business Logistics*, 37 (1), 6-17.

Berg, B. L. (2007). Qualitative research methods for the social sciences. London: Pearson.

Chen, H., Chiang, R.H.L. & Storey, V.C. (2012). Business Intelligence and Analytics: From Big Data to Big Impact. *MIS Quarterly*, 36 (4), 1165-1188.

Craighead, C.W., Hanna, J.B., Gibson, B.J. and Meredith, J.R. (2007) "Research approaches in logistics: Trends and alternative future directions," *The International Journal of Logistics Management,* 18 (1), pp. 22-40.

Davenport, T.H. (2006). Competing on Analytics. *Harvard Business Review*, 84 (1), 98-107.

Davenport, TH and Harris, JG (2007). *Competing on Analytics: The new science of winning*. Boston: Harvard Business Press.

Davenport, T.H. & Patil, D.J. (2012). Data Scientist: The Sexiest Job of the 21st Century. *Harvard Business Review.* http://hbr.org/2012/10/data-scientist-the-sexiest-job-of-the-21st-century/ (accessed 17 March 2014).

Dalkey, N. & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. *Management Science*, 9 (3), 458-467.

Delbecq, A.L., Van de Ven, A.H. & Gustafson, D.H. (1975). *Group techniques for program planning*. Glenview, IL: Scott, Foresman and Co.

Eisenhardt, K.M. (1989). Building Theories from Case Study Research. Academy of Management Review, 14 (4), 532-550.

Ellram, L.M. (1996), "The use of case study method in logistics research," *Journal of Business Logistics,* 17 (2), pp. 93-138.

George G., Haas, M., and Pentland, A., (2014). Big Data and Management. *Academy of Management Journal*, 57(2): 321-326.

Grant, D.B. (2012. *Logistics Management*, Harlow, UK: Pearson Education.

Haug, A. & Arlbjørn, J.S. (2011). Barriers to master data quality. *Journal of Enterprise Information Management*, 24 (3), 288-303.

Hazen, B.T., Boone, C.A., Ezell, J.D. & Jones-Farmer, L.A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, 154, 72-80.

INFORMS (2016). What is Analytics? *INFORMS*. https://www.informs.org/About-INFORMS/What-is-Analytics (accessed 22 November 2016).

Jacobs, J.M. (1996). *Essential assessment criteria for physical education teacher education programs: A Delphi study*. Unpublished doctoral dissertation. Morgantown: University of West Virginia.

Kauffman, S. (1993). *The Origins of Order*. Oxford: Oxford University Press.

Kauffman, S. (1996). *At Home in the Universe*. Oxford: Oxford University Press.

Keil, C., Cule, P.E., Lyytinen, K. & Schmidt, R.C. (1998). A framework for identifying software project risks. *Communications of the ACM,* 41 (11), 76-83.

Kiron, D., & Shockley, R. (2011). Creating Business Value with Analytics. *MIT Sloan Management Review,* 53 (1), 57-63.

Kvale, S. & Brinkmann, S. (2009). Interviews. *Learning the Craft of Qualitative Researcch Interviewing*. (2nd Ed.).Thousand Okas, CA: Sage.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S. & Kruschwitz, N. (2011). Big Data, Analytics and the Path from Insights to Value. *MIT Sloan Management Review,* 52 (2), 21-32.

Lazer, D, Kennedy, R, King, G & Vespignani, A 2014, 'The parable of Google Flu: Traps in big data analysis', *Science*, vol. 343, no. 6176, pp. 1203–1205.

Leavitt, H.J. (1965). Applying organizational change in industry: Structural, technological and humanistic approaches, in J.G. March (Ed.) *Handbook of Organizations*. Chicago, IL: Rand McNally, XX-XX.

Lindgreen, A., Hingley, M., Grant, D.B. & Morgan, R.E. (2012). Value in business and industrial marketing: Past, present, and future. *Industrial Marketing Management*, 41 (1), 207-214.

Mangan, J., Lalwani, C. and Gardner, B. (2004), "Combining quantitative and qualitative methodologies in logistics research," *International Journal of Physical Distribution & Logistics Management,* 34 (7), pp. 565-578.

McAfee, A. & Brynjolfsson, E. (2012). Big Data: The Management Revolution. *Harvard Business Review*, 90, 60-68.

McAfee, A. (2006). Mastering the Three Worlds of Information Technology. *Harvard Business Review*, 84, 141-149.

McKinsey (2011). *Big data: The next frontier for innovation, competition, and productivity*. http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation, (accessed 17 March 2014).

McKenna, H.P. (1994). The Delphi technique: a worthwhile research approach for nursing? *Journal of Advanced Nursing*, 19 (6), 1221-1225.

Melnyk, S.A, Bititci, U., Platts, K., Tobias, J. & Anderson. B. (2014). Is performance measurement and management fit for the future? *Management Accounting Research*, 25, 173–186.

Miles, M.B. & Huberman, M. (1994), *Qualitative Data Analysis: An Expanded Sourcebook.* (2nd ed.). Thousand Oaks, CA: Sage.

Mortenson, M.J., Doherty, N.F. & Robinson, S. (2015), Operational research from Taylorism to Terabytes: A research agenda. *European Journal of Operational Research*, 241, 583-595.

Nerur, S., Mahapatra, R. & Mangalaraj, G. (2005). Challenges of migrating to agile methodologies. *Communications of the ACM*, 48 (5), 72-78.

Ohm, P. (2010). Broken Promises of Privacy: Responding to the Surprising Failure of Anonymization. *UCLA Law Review*, 57 (6), 1701-1777.

Okali, C. & Pawlowski, S.D. (2004). The Delphi method as a research tool: an example, design considerations and applications. *Information & Management,* 42, 15-29.

Operational Research Society (2016). What is O.R.? *Learn About O.R.* http://www.learnaboutor.co.uk/ (accessed 22 November 2016).

Pandey, S.K. (2016). Extracting Market Value of Business and business Decision from Big data Analytics. *International Journal of Computer Applications*, 133 (1), 29-32.

Pape, T. (2016). Prioritising data items for business analytics: Framework and application to human resources. *European Journal of Operational Research*, 252, 687-698.

Paré, G., Cameron, A.F., Poba-Nzaou, P. & Templier, M. (2013). A systematic assessment of rigor in information systems ranking-type Delphi studies. *Information & Management*, 50, 207-217.

Penrose, E. (1959). *The Theory of the Growth of the Firm.* Guildford, UK: Billing and Sons Ltd.

Ranyard, J.C., Fildes, R. & Hu, T-I. (2015). Reassessing the scope of OR practice: The Influences of Problem Structuring Methods and the Analytics Movement. *European Journal of Operational Research*, 245, 1-13.

Schmidt, R.C. (1997). Managing Delphi surveys using nonparametric statistical techniques. *Decision Sciences Journal,* 28 (3), 763-774.

Schoenherr, T. & Speier-Pero, C. (2015). Data Science, Predictive Analytics and Big Data in Supply Chain Management: Current State and Future Potential. *Journal of Business Logistics*, 36 (1), 120-132.

Shanks, G. & Bekmamedova, N. (2012). Achieving benefits with business analytics systems: An evolutionary process perspective. *Journal of Decision Systems,* 21 (3), 231-244.

Strauss, A. & Corbin, J. (1998), Basics of Qualitative Research: Grounded Theory Procedures and Techniques. Thousand Oaks, CA: Sage.

Strong, R., Lee, Y. & Wang, R. (1997). Data Quality in Context. *Communications of the ACM*, 40 (5), 103-110.

Thorp, J. (1998). *The Information Paradox*. Montréal: McGraw-Hill.

Vessey, I., & Ward, K., (2013). The Dynamics of Sustainable IS Alignment: The Case for IS Adaptivity. *Journal of the Association for Information Systems*, 14 (6): 283-311.

Vidgen, R. (2014a). Making Connections with Big Data. *Hull Analytics Workshop*, 15 July 2014. University of Hull, UK. https://datasciencebusiness.wordpress.com/2014/07/21/big-data-and-business-analytics-workshop-report/

Vidgen, R. (2014b). Creating business value from big data and business analytics: Organizational, managerial and human resource implications. Project Report for, *NEMODE* (New Economic Models in the Digital Economy). http://www.nemode.ac.uk/?page_id=1062

Vidgen, R. & Morton, J. (2014). Creating value from Big Data and business analytics: the organisational challenge. Making an Impact workshop, *OR56 Annual Conference*, 9-11 September 2014, Royal Holloway, UK.

http://www.theorsociety.com/Pages/Conferences/OR56/OR56MakingWorkshop.aspx#6

Vidgen, R., & Wang, X. (2006). From business process management to business process ecosystem. *Journal of Information Technology*, 21: 262-271.

Vidgen, R. & Wang, X. (2009). Coevolving systems and the organization of agile software development. *Information Systems Research*, September, 20 (3), 355-376.

Von der Gracht, H.A. (2012). Consensus measurement in Delphi studies: Review and implications for future quality assurance. *Technological Forecasting & Social Change*, 79, 1525-1536.

Waller, M.A. & Fawcett, S.F. (2013). Click Here for a Data Scientist: Big Data, Predictive Analytics, and Theory Development in the Era of a Maker Movement Supply Chain. *Journal of Business Logistics*, 34 (4), 249-252.

Wang, G., Gunasekaran, A., Ngai, E.W.T. & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, 176, 98-110.

Watson, M. (2014). Three things you should know about big data and analytics. *CSCMP's Supply Chain Quarterly*, http://www.supplychainquarterly.com/print/20141107-three-things-you-should-know-about-big-data-and-analytics/ (accessed 14 January 2015).

Willis, J.W., Jost, M. & Nilakanta, R. (2007). Foundations of Qualitative Research: Interpretive and Critical Approaches. Thousand Oaks, CA: Sage.

Yin, R. (2009). *Case Study Research.* (4th ed.). Thousand Oaks, CA: Sage.

Yui, C., (2012). The Big Data Opportunity: making government faster, smarter and more personal. London: The Policy Exchange.

Zikopoulos. P., Eaton, C., DeRoos, D., Deutsch, T. & Lapis, G. (2012). *Understanding Big Data: Analytics for Enterprise Class Hadoop and Streaming Data*. Maidenhead, UK: McGraw-Hill.

Appendix A: Delphi survey design

The Delphi survey consisted of 31 items and was implemented using Qualtrics (www.qualtrics.com). Pilot testing demonstrated that to rank all 31 items would be a taxing task and would lead to poor quality data and high non-completion rates. To avoid the cognitive overload of ranking 31 items the survey was divided into two parts. First, respondents were asked to select their top 10 items from the bank of 31 (Figure A.1). Hovering over an item brought up an on-screen pop-up description of that item (see Appendix B for item descriptions).

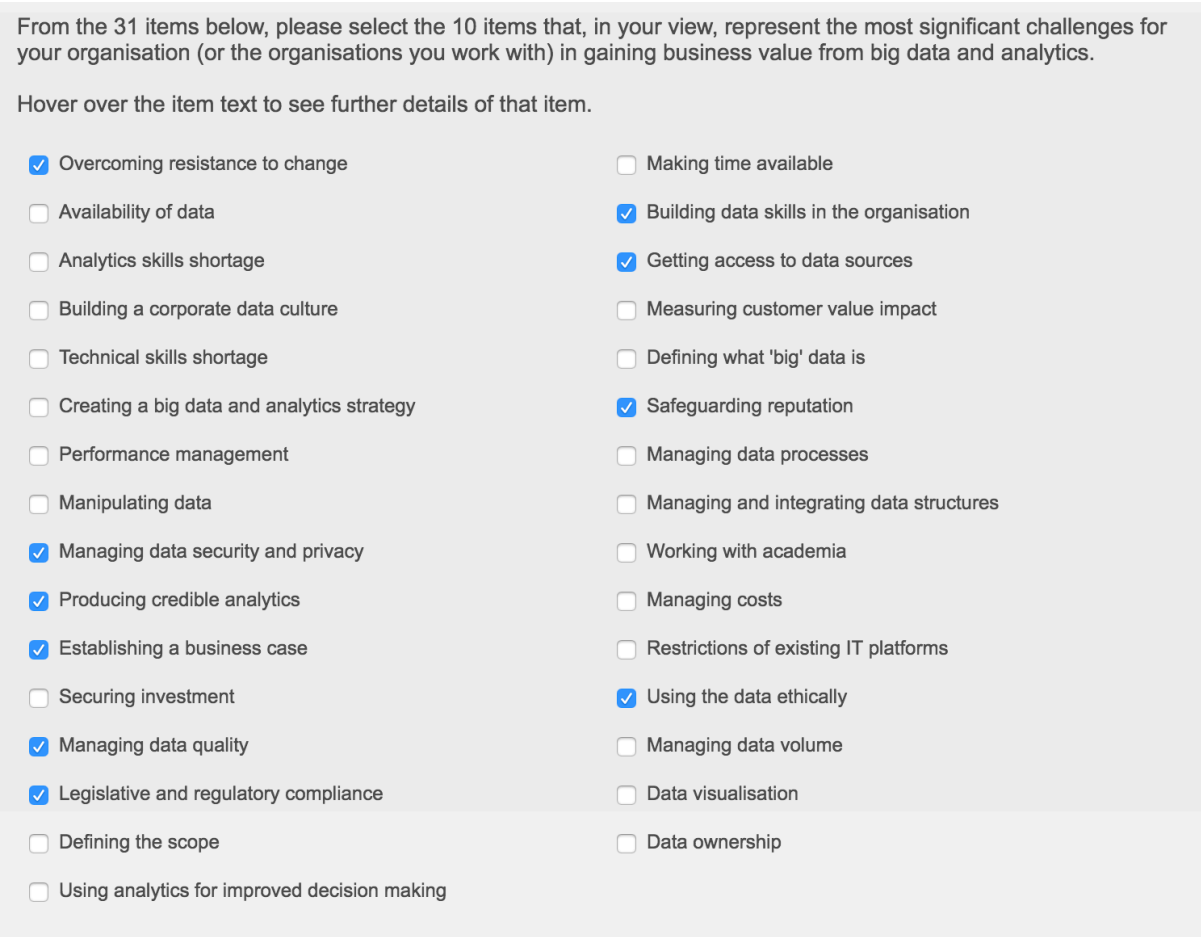

Figure A.1: Stage 1 – illustration of selection of top 10 items

Having selected 10 items, respondents were then presented with their 10 items and asked to use 'drag and drop' to reorder the items according to importance (Figure A.2). Respondents could navigate back and forward through the survey to adjust their selection at any time. In the third stage respondents were asked for demographic information.

In subsequent rounds respondents were presented with all 31 items in ranked order and asked to use drag and drop to reorder the items as they saw fit.

The Delphi study reached convergence on the second round (see Appendix B for details).

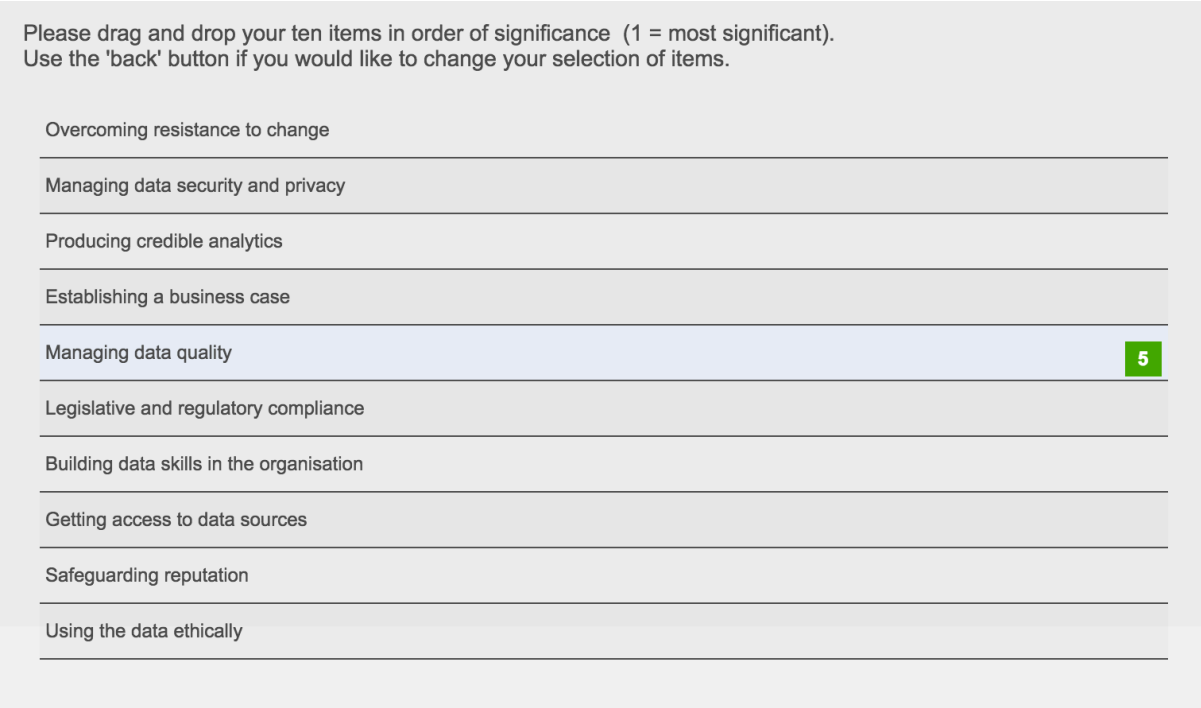

Figure A.2: Stage 2 – ranking of top 10 items

Appendix B: Delphi study rankings

		Ranking	
Item	**Description**	**Round 1 (N = 72)**	**Round 2 (N = 41)**
Managing data quality	assuring data quality aspects, such as accuracy, data definitions, consistency, segmentation, timeliness, etc.	1	**1**
Using analytics for improved decision making	linking the analytics produced from big data with key decision making in the business	2	**2**
Creating a big data and analytics strategy	having a clear big data and analytics strategy that fits with the organisation's business strategy	3	**3**
Availability of data	the availability of appropriate data to support analytics (does the data exist?)	5	**4**
Building data skills in the organisation	the training and education required to upskill employees in general to utilise big data and analytics	6	**5**
Restrictions of existing IT platforms	existing IT platforms/architecture may make it difficult to migrate to and manage big data and analytics	4	**6**
Measuring customer value impact	can the real impact on the customer of managing big data be measured?	8	**7**
Analytics skills shortage	difficulty in acquiring the mathematical, statistical, visualisation skills for producing analytics	7	**8**
Establishing a business case	can 'tangible' benefits of big data be demonstrated (e.g., return on investment)?	10	**9**
Getting access to data sources	accessing appropriate data sources to produce and manage big data (can the data be accessed?)	9	**10**
Producing credible analytics	are the analytics produced from big data likely to be credible and trusted by the organisation?	11	11
Building a corporate data culture	e.g., are data and analytics taken seriously enough by the leaders at a strategic level in the business?	13	12
Making time available	will people have enough time to work with big data and analytics, over and above the 'day job'?	12	13
Managing data processes	managing the complexity of big data processes (e.g. generating, storing, cleaning data and producing analytics)	14	14
Technical skills shortage	difficulty in acquiring technical/IT skills for managing big data and operationalising analytics	15	15
Overcoming resistance to change	is there buy-in and engagement around the benefits of big data (the 'so what?')? Can barriers to change be overcome?	16	16
Managing and integrating data structures	data held in different business silos, systems and segmented in various ways is difficult to structure for analysis	18	17
Managing data security and privacy	ensuring that data is stored securely, only available to intended recipients, and anonymised as needed	17	18
Data visualisation	ability to display and visualise the data to communicate insights clearly within the organisation	21	19
Managing data volume	does the organisation have effective ways (systems) for storing and managing large volumes of data	19	20
Data ownership	who owns the big data? Inside (e.g., which department) and outside of an organisation (e.g., Government, partners)	20	21
Managing costs	ability to manage the costs associated with big data	22	22
Defining the scope	difficulty in defining the scope of big data projects in the organisation (where does it start and stop?)	23	23
Defining what 'big' data is	difficulty in defining what 'big data' actually is	24	24
Securing investment	ability to secure the investment needed to build big data and analytics (infrastructure, skills, training, etc.	25	25
Manipulating data	being able to process the data to produce analytic insight	26	26
Legislative and regulatory compliance	compliance with laws such as the Data Protection Act 1998/2003	27	27
Using the data ethically	using the data in an ethical way and ensuring all areas of the organisation are using it in acceptable ways	28	28
Performance management	ability to develop key indicators for big data and analytics performance reporting	29	29
Safeguarding reputation	e.g., reputation and brand damage caused by inappropriate use of data, data leakage, selling data	30	30
Working with academia	can the organisation build relationships and work effectively with academia?	31	31